USE OF WEATHER VARIABLES FOR PREDICTING FALL COVEY CALLING RATES OF NORTHERN BOBWHITES

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ABSTRACT

A newly developed technique for estimating fall northern bobwhite (*Colinus virginianus*) density is currently being employed in parts of the United States. One aspect of this technique involves predicting morning covey calling rates (i.e., the proportion of coveys that call on a given morning). We monitored 60 radiomarked coveys, a total of 229 covey observations, to determine whether or not each covey called. Calling rates were evaluated in relation to date, year, area, temperature, relative humidity, barometric pressure, barometric status, cloud coverage, and wind speed. We used logistic regression to test 9 *a priori* models as predictive models of bobwhite covey calling behavior. Models were compared using Akaike information criteria (AICc) values to determine the relative importance of 6 different variables (wind speed, date, temperature, cloud coverage, barometric pressure, and relative humidity). An exploratory analysis was then conducted to find the best predictive model using the best subsets model selection procedure. Standard errors of the coefficients in the best models were calculated using a traditional bootstrapping technique. We found an overall calling rate of 78%. Wind speed and date were the most influential of the 6 variables used in *a priori* model tests. Nine of the 19 exploratory models fit the data reasonably well. The best model included area and wind speed as independent variables, and was a better model than the best *a priori* model. There was a difference in calling rates between areas, and as a consequence, we recommend caution in application of our models to new areas.

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Key words: calling rate, *Colinus virginianus,* covey calls, density estimation, Missouri, northern bobwhite, weather

INTRODUCTION

Various methods have been evaluated for counting bobwhites during the fall season, including covey mapping, mark-recapture techniques, drive counts (Dimmick et al. 1982, Janvrin et al. 1991), and distance sampling (Guthrey 1988). These methods have unique biases and are often imprecise or unreliable. Norton et al. (1961) evaluated several papers and determined summer whistling cock counts did not provide reliable indices of fall populations. Distance sampling has been found to be a poor estimator of bobwhite populations when density is low (Kuvlesky et al. 1989). Drive counts can be reasonable estimators of bobwhite density (Dimmick et al. 1982, Janvrin et al. 1991) but are logistically difficult because of large labor requirements. Mark-recapture techniques have biases and assumptions which often are not met. Each of the above methods is labor and time intensive, and as a consequence, biologists and managers do not have a reliable and cost-effective technique to estimate northern bobwhite abundance during the fall season.

Fall covey calls provide another potential method for counting bobwhites (Guthrey 1986). Bobwhites form coveys beginning in fall and these coveys vocalize through winter. By determining the proportion of coveys that call and estimating average covey size, it should be possible to estimate bobwhite abundance by counting the number of coveys heard on an area. DeMaso et al. (1992) found that covey calls provided a poor density estimate when using a single observer and an unknown sampling area. Recent research indicates the morning covey call count method, which involves counting calling coveys on a known area, has potential as a density estimator (Wellendorf 2000). This method is currently being used in the southeastern United States and parts of Missouri.

To estimate bobwhite density using the covey call count technique, it is necessary to estimate the proportion of coveys that call (or calling rate) on the mornings data are collected. This paper focuses on predicting the proportion of coveys that call on a given morning.

The morning covey calling rate is defined as the proportion of coveys from which at least 1 bird calls on a given morning. This calling rate is not constant over time (W. E. Palmer, Tall Timbers Research Station, personal communication), and we hypothesize that environmental factors, such as time of year and weather, influence this variation. No previous literature was found showing correlation of fall covey calling with environmental factors, but several papers exist relating courtship whistles from males in the summer with weather variables. Hansen and Guthrey (2001) reported whistling activity detected by observers decreased as temperature, light intensity, and wind speed increased, and increased as humidity increased. Robbins (1981) found a positive correlation between number of bobwhite whistles detected and temperature, and a negative relationship with cloud coverage. Robel et al. (1969) found significant correlation between the number of whistles heard and temperature, relative humidity, wind velocity, and date, but noted little effect from changes in barometric pressure and light intensity. Bennitt (1951) reported a significant effect of temperature on bobwhite whistling behavior, while Elder (1956) reported no effect of temperature. These papers present conflicting results and none identifies whether environmental variables affect bobwhite calling behavior, or if calling activity is only altered as perceived by observers.

Using radiotelemetry, we positioned observers within hearing distance of a known covey location and observed the calling activity of that particular covey. We measured weather variables during the calling period, and built logistic regression models to determine the relationships of those variables to covey calling behavior. An exploratory model was also built in an attempt to find the best predictive model for use with the morning covey call count population estimation technique.

METHODS AND STUDY AREAS

Study Areas

The data were collected on Reform and Whetstone Creek Conservation Areas in Callaway County, Missouri. The Whetstone Creek Conservation Area study area (WCCA) has a gently rolling terrain and contains approximately 500 ha of upland habitat consisting of about 20% forest and 80% open fields. The area is intensively managed for small game, including northern bobwhites. Management practices include row cropping, discing, and burning. Reform Conservation Area (RCA) is owned by Union Electric Company and managed by the Missouri Department of Conservation. The RCA study area is approximately 500 ha, about 30% wooded and 70% open, and consists of grazed pastures, crop fields, and woody draws.

Fall Covey Call Data

Radiomarked coveys were monitored during the fall to determine whether or not each covey called (≥1 bird called) on each morning they were observed. Sampling was conducted from October through mid-November 1999, and mid-September through mid-November 2000. Radiomarked coveys (≥2 bobwhites, at least 1 being radiomarked) were randomly selected for monitoring without replacement. Once all radiomarked coveys had been monitored, they were re-randomized and sampled again. We added new radiomarked coveys after all coveys already scheduled for sampling had been monitored. If 2 coveys chosen for sampling were within 1 km of each other, the covey chosen second was sampled the following day to insure independent data. Observers began listening ≥40 minutes prior to sunrise, and all covey calls were recorded until 10 minutes after the last covey call was detected, or sunrise, whichever came first.

Observers stood about 50 m from each chosen covey. Coveys located <20 m or >150 m from the observer were not used in the analysis. We assume 100% detection, and no observer influence on calling behavior of coveys >20 m and <150 m from the observer. We attempted to observe morning covey calling activity 7 days/week, weather permitting. We did not collect data during rain or during wind speeds >33 kmph. Because only 1 to 5 birds in most coveys were radiomarked, we assume radio transmitters did not affect calling behavior of coveys. We also made the assumption that individual coveys do not inherently call at different rates.

Independent Variables

Weather variables were collected at the Prairie Fork Creek Conservation Area Weather Station each day at the hour closest to sunrise. This weather station was located about mid way between the most distant points on WCCA and RCA. All study areas were <16 km from the weather station, so variation in weather variables from the data collected should have been minimal.

The variables collected at the weather station included wind speed (kph), temperature (°C), relative humidity (%), and barometric pressure (mb Hg at sea level). Barometric status was computed by determining the trend in barometric pressure from the previous 3 hours. Percent cloud cover was estimated by each observer at sunrise and averaged to the nearest 20% to obtain a single estimate of cloud cover for each morning.

Other variables used in the analysis included date, year, and area. We categorized date into 9 weekly periods (hereafter referred to as week) to insure we had enough observations in each period to allow maximum variation in calling rates. Year was included in the analysis because the fall of 1999 was unusually warm and dry, whereas the fall of 2000 was relatively normal for central Missouri. Area was included because environmental factors may have varying influences on different areas.

Statistical Analysis

Univariate Analysis.—The response variable (call) was plotted on a graph with each independent variable separately and visually inspected for trends. If a nonlinear trend was detected, the variable was transformed from its linear form to a form that fit the data better, and tested using least squares from a univariate logistic regression.

A Wilcoxon 2-sample test (Snedecor & Cochran 1989) with significance at $\alpha = 0.05$ was performed on each independent variable with the response variable. The Wilcoxon test was used instead of a t-test because some of the variables could have had non-normal distributions. These univariate tests were performed to get a preliminary idea of the relationships between the independent variables and the dependent variable (call). Even if a variable did not show significance, it was used in the models because there was potential for significant interactions with other variables.

Logistic Regression.—Previous researchers (Bennitt 1951, Robel et al. 1969, Robbins 1981, Hansen and Guthrey 2001) reported 6 variables (temperature, relative humidity, wind speed, percent cloud cover, barometric pressure, and date) that influence male whistling during summer. We developed 9 *a priori* models using these 6 variables. Our models were analyzed using logistic regression in program SAS (SAS Institute Incorporated, 1989), with ''called'' or ''did not call'' as the binary response variable. For each *a priori* model, AICc (Akaike Information Criteria for small samples) values were calculated:

$$\mathrm{AICc} = -2\mathrm{loge}(\mathrm{l}(\hat{\mathrm{O}})) + 2\mathrm{K} + 2\mathrm{K}(\mathrm{K} + 1)/(\mathrm{n} - \mathrm{K} - 1)$$

where $\mathrm{loge}(\mathrm{l}(\hat{\mathrm{O}}))$ is the value of the log-likelihood given the data, and K is the number of parameters in the model (Burnham and Anderson 1998). These models were then ranked based on their ΔAIC values (Burnham and Anderson 1998):

$$\Delta\mathrm{AIC} = \mathrm{AICc}i - \min \mathrm{AICc}$$

where AICci = the AICc value for that model and min AICc = the lowest AICc value from all models. A model with a lower ΔAIC value is considered a better model.

Previous research results were not used verbatim as our models because of strong contradictions among the reported results. Instead, our models were built with only 1 variable difference between models to allow the maximum number of direct comparisons between variables. Each variable can be compared to 4 other variables using our models. The number of occasions 1 variable provided a better model than another variable was counted and used to rank the variable's relative importance as influencing factors in fall covey calling behavior.

Exploratory Analysis.—After ranking the relative importance of the 6 variables used in *a priori* models, week, wind, temperature, relative humidity, percent cloud cover, barometric pressure, barometric status, year, and area were all used in a best subsets model selection procedure to pick the best models (Hosmer and Lemshow 1989). The variables year, barometric status, and area were not included, or were not significant in previous literature (Bennitt 1951, Robel et al. 1969, Robbins 1981, Hansen and Guthrey 2001), but we thought they may affect calling, so we tested these variables in our exploratory analysis. These models were run in SAS and AICc and ΔAIC values were calculated for each model (Burnham and Anderson 1998). The continuous main effects variables in each model were tested for interaction effects by adding the interaction terms to the model 1 at a time (Hosmer and Lemshow 1989). Interaction terms that were significant in the models were retained in the final model. Each variable was removed, 1 at a time from each model to determine if the models improved without a particular variable (Hosmer and Lemshow 1989). If a model improved, the variable was left out. Akaike weights (W) were calculated for all models with ΔAIC values ≤ 2 to determine the probability that each particular model was the best of the tested models (Burnham and Anderson 1998):

$$\mathrm{W}i = \exp(-\tfrac{1}{2}\Delta\mathrm{AIC}i)/\Sigma \exp(-\tfrac{1}{2}\Delta\mathrm{AIC}i)$$

The best *a priori* model was compared with the best model from the exploratory procedure. The exploratory model was expected to perform better than the *a priori* model because we had little information to use when building the *a priori* models due to a lack of literature on fall morning covey calling behavior.

No validation was performed on our models because we did not want to reduce the sample size used to build the models. Instead, a traditional bootstrap was used to determine how much the models would change when built with a slightly different data set, in other words, to determine the stability of the models. Observations were randomly chosen with replacement, from the original data set of 229 observations to develop a new data set. The new data set was used to rebuild the model being tested and the intercept and coefficients were saved to a table. This process was repeated 500 times for each model with ΔAIC value ≤ 2. The tables containing the bootstrapped intercepts and coefficients were used to determine the standard error around the intercept and coefficients for each model (Efron and Tibshirani 1986).

RESULTS

Univariate Analysis

A total of 229 observations was collected from 60 coveys in 83 days of data collection. Each covey was monitored 1–10 times, 3.8 being the mean. The covey being observed called 182 times and did not call 47 times. During our study, coveys initiated calling between 9 and 48 minutes before sunrise. More observations were obtained on WCCA (169) than on RCA (60), partly because we were able to trap more coveys on WCCA.

Calling rates were 70.0% (± 0.76%) on RCA, 82.8% (± 0.22%) on WCCA (Fig. 1), and the overall mean was 79.5%. On average, the calling rate on both areas was about 6% higher in 1999 than in 2000, however, there was considerable variation in the calling rate both years (Fig. 2).

A graph of calling by week shows a slight curve

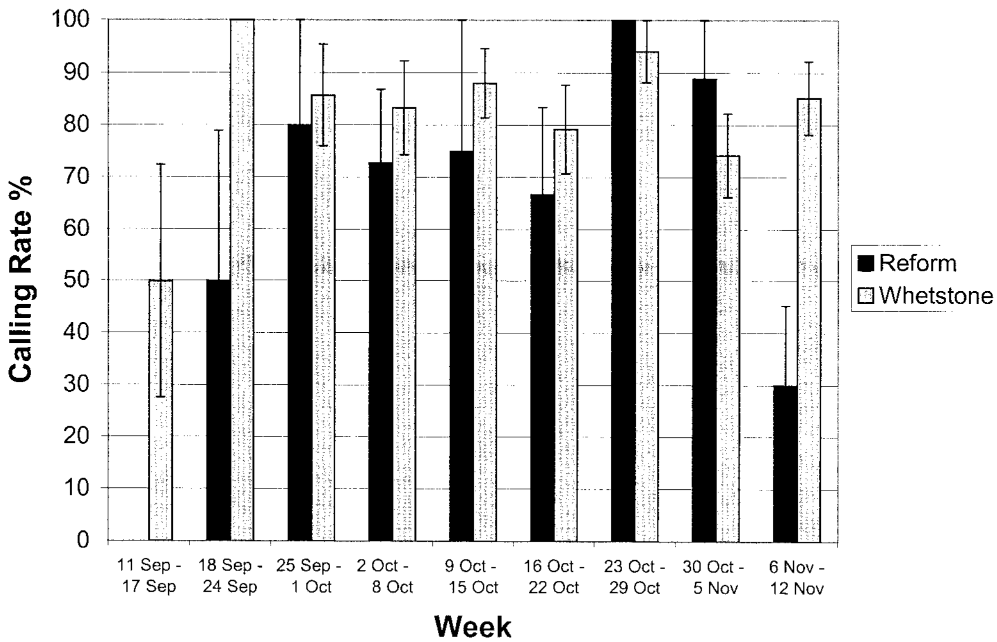

Fig. 1. Weekly morning covey calling rates (± 1 standard error) of northern bobwhite on RCA and WCCA for combined years 1999 and 2000. The calling rate is the proportion of coveys heard calling. No data were collected on RCA during the first week.

in the data (Fig. 3), therefore, week was transformed into a quadratic variable which best fit the data. In all further data analysis, week was used in its quadratic form. The peak calling period was 23–29 October with a calling rate of 96%. The period with the lowest calling rate (50%) occurred during 11–17 September.

Graphs of calling rate by wind speed and by area showed minor linear trends. Calling rate differed by area according to the Wilcoxon test ($P = 0.035$). Mean wind speed differed for calling and non-calling coveys (Table 1), although it was not significant ($P = 0.249$). No other variables were significant in the univariate analysis.

Logistic Regression

None of the overall *a priori* models was a significant predictor of morning covey calls. For these models, AICc values ranged from 235.3 to 239.7, and the intercept only model was 234.5. The ΔAIC values ranged from 0 to 4.36 (Table 2).

Comparisons of the different models showed that

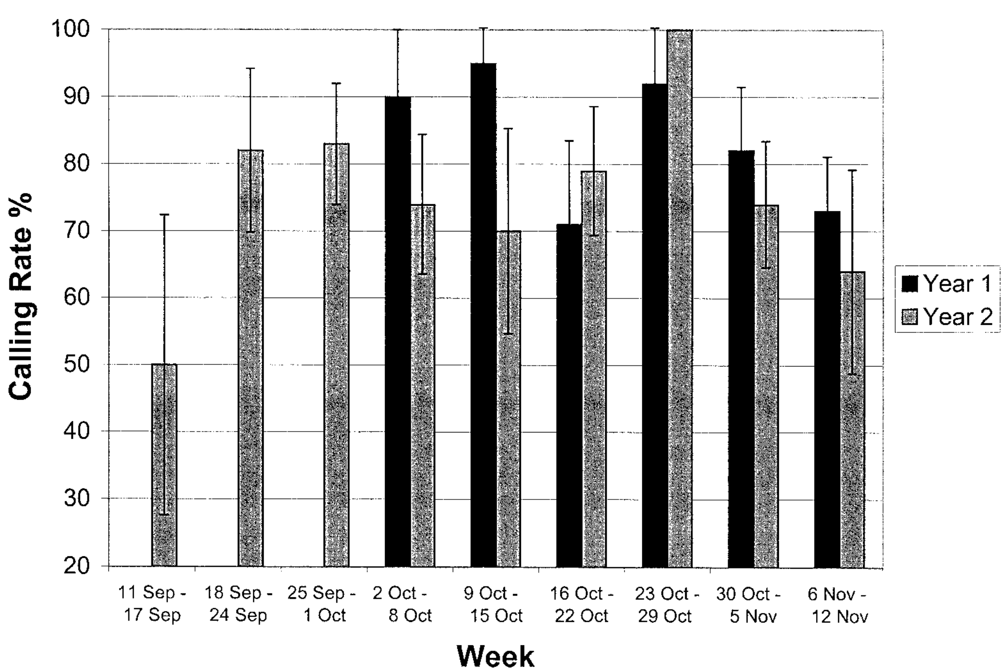

Fig. 2. Central Missouri weekly morning covey calling rates (± 1 standard error) of northern bobwhite during 1999 and 2000. In 1999, no data were collected during the first 3 weeks. The calling rate is the proportion of coveys heard calling.

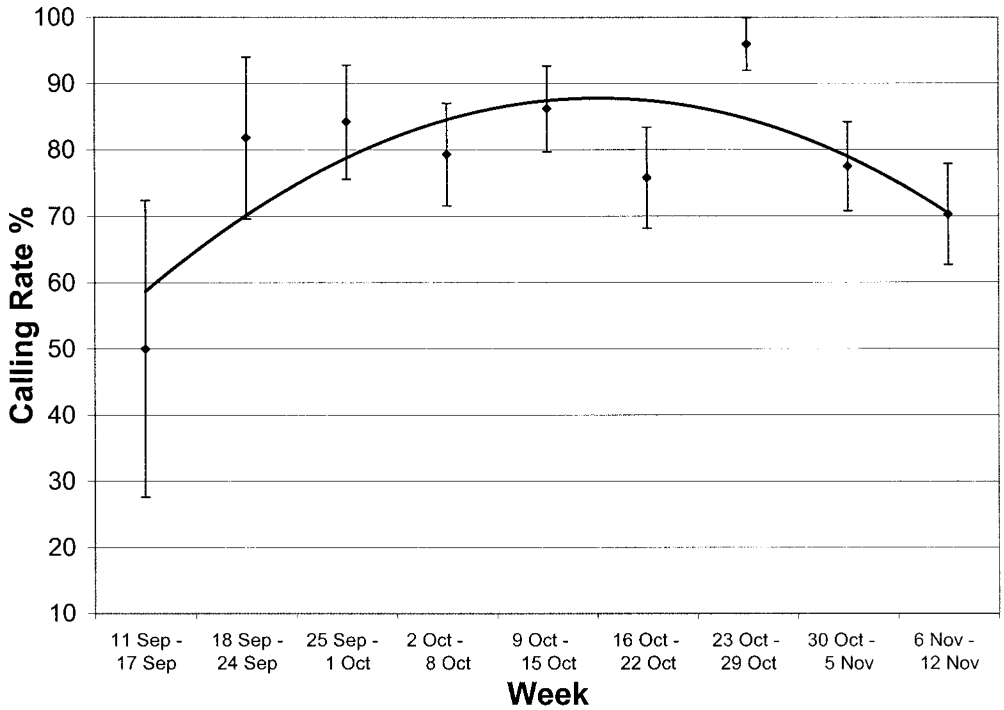

Fig. 3. Weekly morning covey calling rates (± 1 standard error) of northern bobwhite in central Missouri during 1999 and 2000 combined. The calling rate is the proportion of coveys heard calling.

wind speed was the most influential of the 6 variables included in the *a priori* models. Week was the second most influential variable, followed by percent cloud cover for predicting calling behavior. No difference was apparent between the other variables (temperature, relative humidity, and barometric pressure) in their effect on calling behavior. The top 4 models included week and wind, reinforcing the importance of these 2 variables relative to the others.

Exploratory Analysis

The exploratory models had AICc values ranging from 229.5 to 239.5, and the intercept only model was 234.5. Nine of the 19 models were reasonable according to their ΔAIC scores (Table 3). When variables were removed from the models 1 at a time, models did not improve. None of the *a priori* models was better than the best exploratory model.

A model with only area as an explanatory variable provided a good model. No other variables alone provided a model as good as area, indicating area was the most influential variable on covey calling behavior (Table 3). Wind speed, week, and year were also influential variables. All models with some or all of these variables were good models, as long as area was included (Table 3). The addition of other variables into the model did not improve predictive power. When the variable area was removed from any of the models, it lost predictive power.

Area and wind speed were the explanatory variables in the best model, and the second best model used area and week (Table 3). The fact that area and wind provide a better model than area and week supports our findings from the *a priori* models that wind speed had greater influence on covey calling behavior than week.

The model weights show that the best model has a 16.7% probability of actually being the best model, whereas the second best model had 14.6% probability of being the best model (Table 3). Because several of the models share a similar probability of being the best, it would be best to treat them as equally likely models and use a model averaging technique when predicting covey calling rates.

Table 1. Mean values (± SE) of continuous variables considered for inclusion in logistic regression models comparing observations when northern bobwhite coveys called (n = 182) and observations when coveys did not call (n = 47) in central Missouri during 1999 and 2000.

	Calling		Non-calling		Range	
Variable	$\bar{x}$	SE	$\bar{x}$	SE	Min	Max
Wind Speed (kmph)	2.53	0.20	3.30	0.46	0.6	12.4
Percent Cloud Cover	31.16	2.73	35.65	5.93	0.0	100.0
Temperature (°C)	8.86	0.43	8.52	1.03	−2.9	22.1
Relative Humidity	93.01	0.88	93.34	1.66	50.0	100.0
Barometric Pressure (mb Hg)	1020.7	0.39	1020.7	0.86	1007.0	1036.0

Table 2. Ranking of *a priori* logistic regression models predicting northern bobwhite morning covey calls in central Missouri during 1999 and 2000. Each variable is included in 6 or 7 of the 9 models considered.

No.	Model	*P*-value	AICc	ΔAIC
1	43.850 + 0.754 ∗ Week − 0.067 ∗ Week^2 − 0.136 ∗ Wind − 0.004 ∗ Cloud − 0.043 ∗ Baropres	0.190	235.3	0.000
2	23.866 + 0.715 ∗ Week − 0.064 ∗ Week^2 − 0.153 ∗ Wind + 0.011 ∗ Temp − 0.024 ∗ Baropres	0.211	235.6	0.322
3	0.373 + 0.627 ∗ Week − 0.057 ∗ Week^2 − 0.162 ∗ Wind + 0.016 ∗ Temp − 0.009 ∗ Relhum	0.216	235.7	0.378
4	32.548 + 0.667 ∗ Week − 0.060 ∗ Week^2 − 0.162 ∗ Wind − 0.007 ∗ Relhum − 0.031 ∗ Baropres	0.224	235.8	0.488
5	2.567 − 0.186 ∗ Wind + 0.014 ∗ Temp − 0.016 ∗ Relhum − 0.003 ∗ Cloud	0.333	236.1	0.772
6	25.398 − 0.186 ∗ Wind + 0.015 ∗ Relhum − 0.003 ∗ Cloud + 0.022 ∗ Baropres	0.380	236.5	1.159
7	28.912 + 0.721 ∗ Week − 0.064 ∗ Week^2 + 0.013 ∗ Temp − 0.009 ∗ Relhum + 0.004 ∗ Cloud + 0.028 ∗ Baropres	0.321	236.7	1.415
8	−0.641 + 0.754 ∗ Week − 0.068 ∗ Week^2 + 0.013 ∗ Temp − 0.002 ∗ Relhum − 0.005 ∗ Cloud	0.357	237.2	1.938
9	−2.340 + 0.009 ∗ Temp − 0.005 ∗ Relhum − 0.004 ∗ Cloud + 0.004 ∗ Baropres	0.911	239.7	4.361

* Week − Week^2 = the quadratic for week (1–9), Wind = wind speed (kmph), Cloud = % cloud cover, Baropres = barometric pressure (mb Hg), Temp = temperature (°C), Relhum = % relative humidity.

The standard errors around the intercepts and coefficients of our models determined from bootstrapping were small (Table 3), indicating none of our models varied greatly when a slightly different data set was used to build them.

DISCUSSION

Relative Importance of Variables

Comparisons with previous literature are not valid because of differences in survey methods. The previous researchers (Bennitt 1951, Robel et al. 1969, Robbins 1981, Hansen and Guthrey 2001) were working with male courtship whistling in the summer. Our study monitored morning covey calls in the fall, and the effects of weather variables may be completely different during these 2 time periods. Additionally, previous research (Bennitt 1951, Robel et al. 1969, Robbins 1981, Hansen and Guthrey 2001) studied the number of calls heard by observers, whereas our study evaluated the presence or absence of calling activity of individual bobwhite coveys. Some of the weather variables measured may affect the ability of observers to hear morning covey calls, while not affecting the bobwhite calling behavior.

W. E. Palmer (Tall Timbers Research Station, personal communication) has been studying fall morning covey calls in the southeast United States and found that date was an influential variable on their study areas. Our results showing significant influence of week on covey calling activity concur with Palmer's findings.

Extrapolation to New Areas

The area effect we observed on bobwhite calling might be due to a variety of differences between areas. One potential difference is bobwhite density, which was suggested by W. E. Palmer (Tall Timbers Research Station, personal communication) as one of the most important variables influencing covey calling. Because we wanted a model for use with a density estimation technique, it was not practical to include bobwhite density in the model, therefore we did not measure bobwhite density on our areas. We were, however, able to trap and radiomark 43% more coveys on WCCA than on RCA with equal trapping effort, and this great-

Table 3. The 9 best (of 19) logistic regression models that explained the effects of weather variables on morning covey calling rate of northern bobwhite in central Missouri during 1999 and 2000. All models are designed to predict the probability that a covey will call.

No.	Model	*P*-value	−2loge (1(Ô))	AICc	Weight
1	1.1013(0.0149) + 0.7483(0.0163) ∗ Area − 0.1495(0.0040) ∗ Wind	0.029	225.416	229.468	0.167
2	−0.7930(0.0503) + 0.7398(0.0191) ∗ Week − 0.0681(0.0017) ∗ Week^2 + 0.7715(0.0165) ∗ Area	0.032	223.637	229.742	0.146
3	1.3606(0.0184) − 0.4214(0.0167) ∗ Year + 0.7553(0.0166) ∗ Area − 0.1572(0.0041) ∗ Wind	0.035	223.893	229.998	0.128
4	−0.4006(0.0481) + 0.6518(0.0172) ∗ Week − 0.0600(0.0015) ∗ Week^2 + 0.7830(0.0162) ∗ Area − 0.1175(0.0039) ∗ Wind	0.033	221.976	230.151	0.119
5	0.8473(0.0126) + 0.727(0.0155) ∗ Area	0.040	228.246	230.263	0.112
6	−0.2985(0.0502) + 0.6848(0.0179) ∗ Week − 0.0660(0.0016) ∗ Week^2 + 0.7805(0.0169) ∗ Area − 0.4261(0.0175) ∗ Year	0.038	222.309	230.484	0.101
7	0.1585(0.0557) + 0.5794(0.0188) ∗ Week − 0.0564(0.0017) ∗ Week^2 + 0.7913(0.0181) ∗ Area − 0.1233(0.0043) ∗ Wind − 0.4468(0.0178) ∗ Year	0.036	220.526	230.790	0.086
8	1.0684(0.0175) + 0.7319(0.0165) ∗ Area − 0.3778(0.0162) ∗ Year	0.065	227.000	231.052	0.076
9	−1.2667(0.0677) + 0.7051(0.0192) ∗ Week − 0.0634(0.0017) ∗ Week^2 + 0.7777(0.0163) ∗ Area − 0.1417(0.0042) ∗ Wind + 0.0154(0.0009) ∗ Temp	0.044	221.098	231.362	0.065

* Week − Week^2 = the quadratic for categorized weeks (1–9), Wind = wind speed (kmph), Cloud = % cloud cover, Baropres = barometric pressure (mb Hg), Status = barometric status (0 = falling, 1 = stable, 2 = rising), Temp = temperature (°C), Relhum = % relative humidity, Area = 0 (RCA) or 1 (WCCA), Year = 0 (1999) or 1 (2000).

er trapping success may be an indicator of higher bobwhite density on WCCA.

Regardless of the cause(s) of variation between areas, the importance of area as a variable in our study will make extrapolation of our models to new areas difficult. It may be necessary to build a new model for each new area prior to conducting the covey-call-count-density-estimation technique.

We recommend further research on WCCA and RCA to determine if the area effects remain constant over a period of years. More research on these 2 areas would also help determine the extent of annual fluctuations in calling rates. If calling rates fluctuate widely between years, the value of the covey call count technique as a tool for determining annual population trends would be considerably lower.

During our study all sampling was conducted in the hour before sunrise, and we had few days with wind speeds >8 kmph at that time of the day (Table 1). If we had encountered more days with high winds, wind speed may have been a more influential variable. Although we found no significant influence of other weather variables on covey calling behavior, potential effects of these variables may be apparent at more extreme levels. Therefore, our model's usefulness may be limited to days with similar weather conditions to those we encountered. We are confident, however, that these conditions are common during autumn, and our model could be used if data were collected under similar conditions.

Confidence in the Models

The usefulness of our models is questionable because none had an AICc value much lower than that of the intercept only model. Therefore, density estimates obtained by using our models may not be better than simply using the mean calling rate. Bootstrapping showed that models had little variability when rebuilt with a slightly different data set, but this stability may not be due to good predictive ability. It is possible that bobwhite calling rates do not vary greatly across the range of conditions we sampled, thereby causing the models to be stable, even though they have little predictive ability.

CONCLUSIONS

In conclusion, area, week, wind speed, and year were factors affecting bobwhite covey calling rates on our study areas. It appears that none of these variables had a strong influence on calling behavior over the range of weather conditions that we experienced. Our data indicate bobwhite calling rates varied little under normal weather conditions, which would render the mean calling rate as useful as a predictive model.

When using the morning covey call count, we recommend conducting all sampling in weather similar to conditions encountered during our study, and during the last 3 weeks in October (Julian dates 282–302). During this time, calling rates were at their highest (81.0% on RCA and 86.4% on WCCA), which lead to minimum variation between areas. Attempting to compare call counts obtained from different areas is not advisable until the calling rate of each area is known.

Additional research is planned on RCA over the next 2 years. The data collected will be used to validate our models and to determine the importance of annual fluctuations in covey calling rates. Until further research has been conducted, we recommend using caution when interpreting data from morning covey call counts using our models.

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